Using Voxel Similarity as a Measure of Medical Image Registration

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Abstract

In this paper we present our work on using intensity feature spaces to study the relationship between voxel values in registered and unregistered medical images. By taking a simple image model we predict structures that we might expect to find in an intensity feature space produced from different modality images of the same scene. We show how this structure will be modified by image noise, misregistration and differing point spread functions of the two modalities. We show examples of such structure in feature spaces created from clinically acquired Magnetic Resonance (MR) and Positron Emission Tomography (PET) image data. We show how two simple measures of voxel similarity based on these feature space observations, a modified variance of intensity ratio and the 3rd order moment of the feature space histogram, can be used to quantify image misregistration. The 3rd order moment measure is then used with a genetic optimisation algorithm to automatically register pre and post Gadolinium injection MR images.

1 Introduction

Automating medical image registration is becoming an increasingly important goal. It forms the basis of image processing techniques to combine information from the different modalities which are now frequently acquired for many patients. Such combined representations of patient images have been shown to assist in the interpretation of the complementary information provided by the modalities [1].

One approach to registering visually similar images is to manually or automatically locate a small number of equivalent features such as points or surfaces present in both modalities [1, 2, 3, 4, 5, 6]. This requires either a considerable amount of user interaction or a solution to the difficult problem of reliably and automatically segmenting the same feature from different modalities.

An alternative method which we examine in this paper is to create a measure based on a simple function of all corresponding voxels in the two images at a given orientation. This measure should have a minimum or maximum value at

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registration which we can then search for in the parameter space of the three translations and three rotations using an optimisation technique.

The simplest voxel similarity measure is voxel correlation. For this to be effective there must be a linear relationship between intensities of voxels in the two modalities. This is not the case for common combinations of medical image such as MR-PET and MR-CT and published work using this technique has been less successful than alternative approaches of landmark registration and surface matching.

Another more successful voxel similarity measure, the Variance of Intensity Ratios, proposed by Woods [8, 9] has been used to successfully register both PET-PET and PET-MR image pairs of the brain. The main drawback of this technique for PET-MR registration is the need for manual segmentation of the MR brain image to remove the scalp and skull. We have previously shown that a modification of this measure can be used for skull base MR-CT registration provided there is sufficient axial sampling [10].

Van den Elsen [7] has proposed a method using the correlation of an image intensity ridge operator. By choosing an appropriate scale the bone ridge from MR and CT can be extracted and the two gradient images correlated to find the registration transformation.

The success of these approaches encouraged us to devise a methodology for further investigating voxel similarity measures.

2 Method

We have accurately registered many dozens of medical images using anatomical landmarks [1]. This provides us with a large number of reference datasets with which to evaluate alternative automated registration algorithms. We have devised two techniques for assessing possible voxel similarity measures: feature space sequences and similarity measure plots.

2.1 Structures in Intensity Feature Space

A possible way of examining the effect of misregistration useful for devising appropriate voxel similarity measures is to construct 2D distributions or feature spaces of image intensities (or other voxel features) of two images at registration and for a sequence of known misregistrations for each degree of freedom. We term these feature space sequences. A feature space of two images is a two dimensional histogram of the value of a numerical image feature from one image plotted against the corresponding value from the other image.

The feature space may be constructed from all voxels where there is correspondence (i.e. overlap) between the two images. The image feature is usually voxel intensity, but could also be a derived value such as the output of a gradient operator or texture analysis. A feature space sequence can be calculated for each degree of freedom of the rigid body transformation.

To understand the structure seen in feature space sequences it is informative to calculate the expected appearance using a simple model. Consider a tomographic slice consisting of two regions, a vertical band of uniform intensity surrounded by a uniform background intensity. The image intensities from image modality A, a_{ij}, are given by:

$$a_{ij} = \begin{cases} a_2 & u \leq i < v \\ a_1 & \text{otherwise} \end{cases}$$

and, similarly assuming identical voxel sizes for imaging modality B, image intensities are given by:

$$b_{ij} = \begin{cases} b_2 & u \leq i < v \\ b_1 & \text{otherwise} \end{cases}$$

where u and v are the bounds of the vertical band in the x direction and $0 \leq i < x_{max}$ and $0 \leq j < y_{max}$. This is illustrated in figure 1. A feature space of this

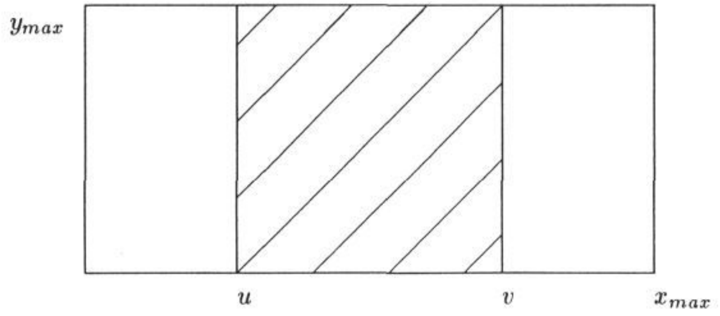

Figure 1: A simple image containing two intensities.

image will consist of two points at coordinates (a_1, b_1) and (a_2, b_2) of intensities equal to the number of voxels within each region with zero elsewhere. With misregistration in the x direction by t pixels two other points will appear at (a_1, b_2) and (a_2, b_1) of intensity ty_{max} as shown in figure 2.

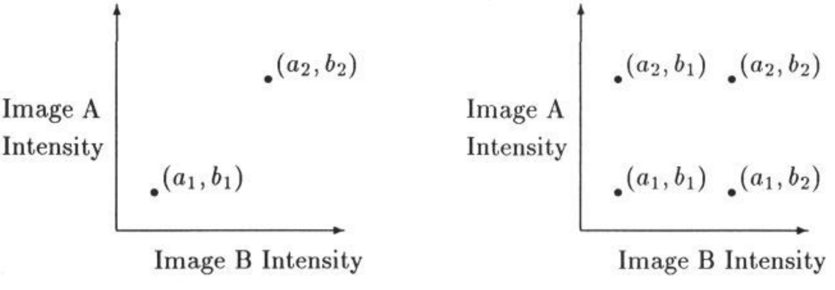

Figure 2: Changes in Feature Space due to misregistration of a simple image. (Left registered, Right misregistered)

With the addition of noise in each modality the feature space image will be convolved with the noise distribution functions of image A and B, in the A and B axes respectively. The feature space with image blurring, by impulse response functions I_{Ar} and I_{Br} in imaging modalities A and B respectively, will consist of the original two high signals at (a_1, b_1) and (a_2, b_2) connected by an arc with the parametric equation in p for the coordinates of arc (a_p, b_p) given by:

$$a_p = a_1 + \sum_{r=u}^{v} I_{A(r-p)}(a_2 - a_1)$$

$$b_p = b_1 + \sum_{r=u}^{v} I_{B(r-p)}(b_2 - b_1)$$

When the blurring functions are the same in the two modalities this parametric equation describes a straight line for $b_1 \leq b_p \leq b_2$ (see figure 3, left) with equation:

$$(a_p - a_1)/(a_2 - a_1) = (b_p - b_1)/(b_2 - b_1)$$

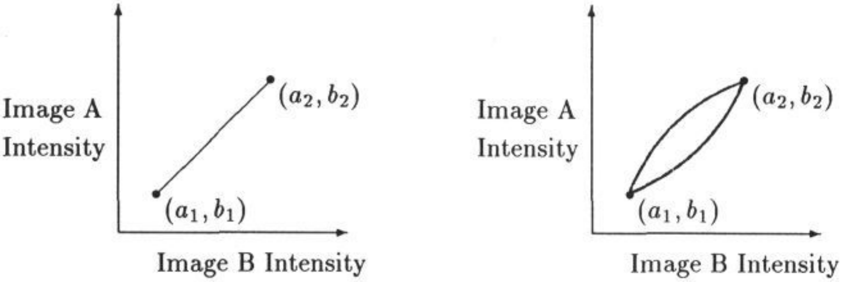

Figure 3: Feature space after image blurring (left registered,right misregistered).

The intensity at each point, p, along this arc in feature space is proportional to the sum of the products of the inverse of the impulse response functions $((I_{A(u-p)}I_{B(u-p)})^{-1} + (I_{A(v-p)}I_{B(v-p)})^{-1})$ and the inverse of the arc length. At misregistration by a distance t in the x direction the parametric equation of the arc becomes:

$$a_p = a_1 + \sum_{r=u}^{v} I_{A(r-p)}(a_2 - a_1)$$

$$b_p = b_1 + \sum_{r=u}^{v} I_{B(r-p-t)}(b_2 - b_1)$$

This equation generates an arc between points (a_1, b_1) and (a_2, b_2) similar in shape to the hysteresis curve of magnetisation of ferromagnetic material (see figure 3, right). The greater the misregistration the greater will be the area enclosed by the curve, until at the limit when the arc will describe the rectangle (a_1, b_1) (a_1, b_2) (a_2, b_2) (a_2, b_1). The area between the two curves is a function of misregistration, contrast between the two regions and the impulse response functions of the two imaging modalities.

In a real image the feature space will consist of a superimposition of a number of points connected by arcs with intensity proportional to image blurring. Image noise will blur the feature space and misregistration will generate hysteresis type curves from the connecting arcs. The misregistration of each boundary element along its surface normal will determine the area enclosed by the corresponding hysteresis curve in feature space. For convoluted structures surface orientations will be widely distributed and the feature space for a particular misregistration will be a superimposition of multiple hysteresis type curves, but the envelope of these curves will correspond to the maximum misregistration perpendicular to any element of the surface.

2.2 Feature Spaces of Clinically Acquired Images

We have generated feature space sequences from various combinations of MR, CT and PET images in the head. In this paper we will concentrate on the structure found in MR-PET and MR-MR combinations. All data was initially registered using our interactive point landmark system [2]. The MR-PET image pair consisted of a T1 weighted (voxel size 0.859mm x 0.859mm x 2.5mm) MR acquisition and an FDG (voxel size 2.0mm x 2.0mm x 3.75mm) PET scan. The MR-MR pair was a T1 weighted pre Gadolinium sequence (voxel size 0.898mm x 0.898mm x 2.0mm) and a T1 post Gadolinium (voxel size 0.898mm x 0.898mm x 1.0mm) image (the patient having been removed from the scanner for injection between scans).

Prior to the creation of the feature spaces the lower resolution image was resampled using tri-linear interpolation upto the resolution of the higher resolution image. For the work presented here all images were filtered with a Hanning window to give a full width half maximum of the impulse response function of 10mm. This reduced the effects of noise and ensured both images contained the same scale of information. All feature spaces shown are calculated on a 256×256 matrix with appropriate binning applied over the range of intensities present in each modality (usually 0-32767 for PET data and 0-4095 for MR data) and are shown with appropriate thresholding to display the low intensity structure.

2.3 Similarity Measures

We have developed two simple registration measures based on observations of the feature space structure. Firstly by limiting the range of intensities used in the two modalities when calculating Roger Woods' coefficient of the variance of intensity ratio for MR and PET registration we hope to remove the need for pre-segmentation of the MR data. Secondly by using the third order moment of a histogram of the feature space values themselves we hope to find a measure sensitive to the overall dispersion in the feature space due to mis-registration.

A simple quantitative indication of the effectiveness of a similarity measure is gained by examining plots of its value as one of the six degrees of freedom is varied around its value at registration. An ideal misregistration measure has a minimum value at registration, and increases monotonically with misregistration. It must be emphasised that this does not sample all of the parameter space, and there are likely to be many local minima (or even the global minimum) that are not visible in the one dimensional plots.

3 Results

3.1 Feature Space Structure

Feature space sequences for the MR and PET-FDG image volumes are shown in figure 4 and 5 and for the MR image volumes with and without Gadolinium in figure 6. These feature space sequences are of very different overall appearance but they share common characteristics predicted in section 2.1:

- Diagonal features, corresponding to blurring between adjacent regions in the image volumes, disperse with misregistration.
- The hysteresis type patterns show clear bounds, presumably caused by the maximum misregistration along surface normals.
- Except at the origin, the brightest feature space pixels decrease in intensity with misregistration.
- The number of low intensity feature space pixels increases with misregistration.

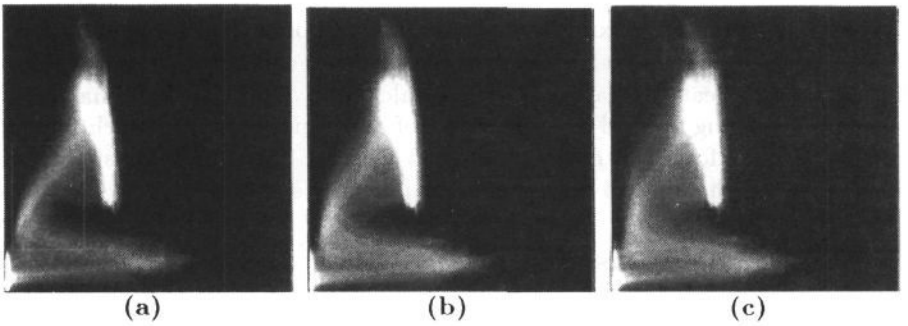

Figure 4: Feature spaces created from a misregistered MR (horizontal scale) and PET (vertical scale) image pair: (a) registered, (b) x axis (cranio-caudal) rotation of 5 deg., (c) x axis rotation of 10 deg.

3.2 Similarity Measures

Figure 7(a) shows the cost function with misregistration generated from the variance of intensity ratios for the PET-FDG and MR image volumes (PET-FDG intensity divided by MR intensity). The functions are reasonably well behaved with monotonically increasing cost with misregistration except for x and z rotations. Also for x and y translations the cost function starts to decrease once misregistration exceeds about 5mm which is probably related to the resolution distance of the image volumes. Figure 7(b) shows that, by selecting a predefined band of intensities to perform the analysis, the cost function for x and z rotations are considerably improved. The intensity ranges used in the MR and PET are shown in figure 4(a). Figure 8 shows the cost functions for the pre and post Gadolinium

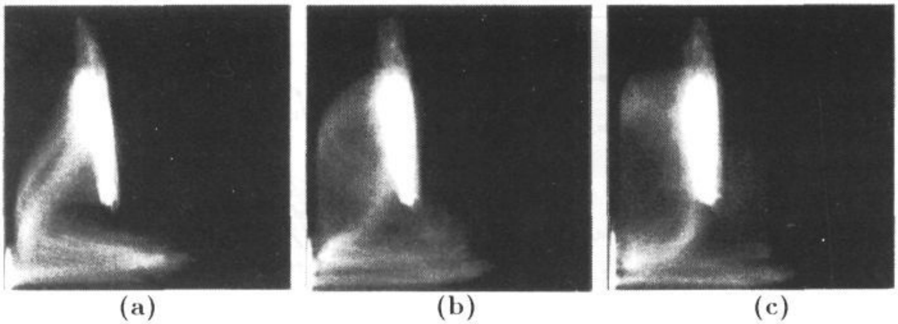

Figure 5: Feature spaces created from a misregistered MR (horizontal scale) and PET (vertical scale) image pair with a lateral translation of 2mm (a), 4mm (b) and 10mm (c).

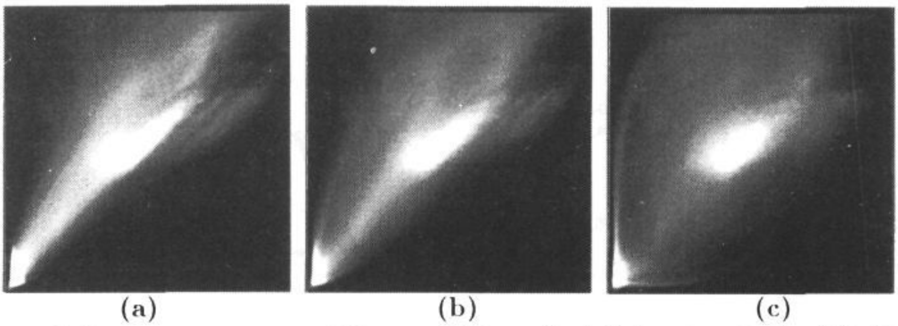

Figure 6: Feature spaces created from an MR pre Gadolinium (vertical scale), MR post-Gadolinium (horizontal scale) image pair: (a) registered,(b) lateral translation of 2mm and (c) 5mm.

MR image volumes calculated using the thrid order moment of the feature space histogram. These plots demonstrate that the cost increases almost monotonically with misregistration in each of the degrees of freedom. These image volumes have been successfully registered automatically with this cost function using a genetic algorithm[11] with a population size of 100 and 30 generations, at two scales.

4 Discussion

We have devised a methodology for further evaluation of voxel similarity measures, in particular the generation of feature space sequences. All the feature space sequences produced shared common types of structure which may provide strong cues for registration. The two simple measures we have developed based on our feature space observations have shown improved sensitivity to image misregistration.

The observed cues only exist when registration of surface features is within the resolution distance of each image. One possible approach may be to blur

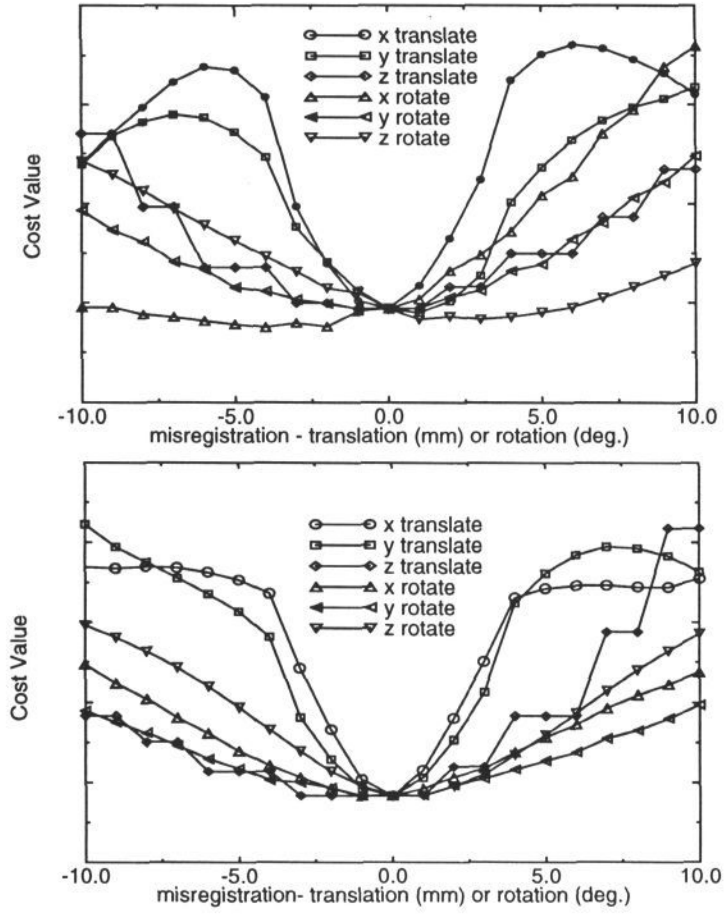

Figure 7: Cost functions calculated using the Variance of Intensity Ratios of the MR-PET image pair using the full range of intensities (top), and a limited range of intensities (bottom).

images to a greater extent in a multiscale approach. Work is currently underway to investigate the effects of varying scale on feature space structure. Alternatively feature spaces created from gradient operators such as those used by Van den Elsen [7] may provide more powerful registration cues.

One limitation of the voxel similarity approach to registration is that at any particular orientation the measure is only a function of the region of overlap of the two images. This is often a problem with clinically acquired data when one of the datasets covers a much more restricted volume than the other. The measure does not continue to increase with misregistration when there is no area of overlap of corresponding objects in the two datasets.

These types of registration measure are robust to many types of noise because they are performed on large numbers of image voxels. They may be particularly suited to the problem of local re-registration to correct for geometric distortion. An

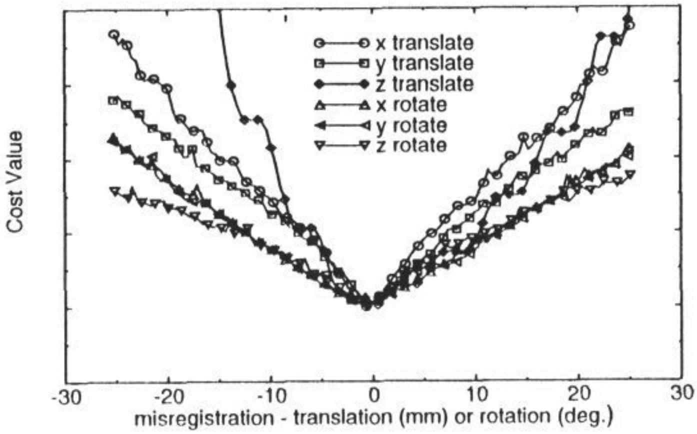

Figure 8: Cost function calculated using the 3rd order moment of the feature space histogram of a pre-Gadolinium and post-Gadolinium image pair.

example would be the use of CT data to correct MR image distortion following a global registration of the two. It is important to understand the types of distortions that can occur before these types of corrections can be applied. More work is needed to devise and test appropriate similarity measures, but the approach shows great promise for producing an accurate, automated method for registration of voxel datasets in 3D medical imaging.

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References

[1] Hill DLG,Hawkes DJ,Gleeson MJ, Cox TCS, Strong AJ, Wong W-L,Ruff CF, Kitchen ND, Thomas DGT, Sofat A, Crossman JE, Studholme C, Gandhe A, Green SEM, Robinson GP. *Accurate frameless registration of MR and CT images of the head: Applications in Planning Surgery and Radiotherapy. Radiology* 191:447-454. 1994

[2] Hill DLG, Hawkes DJ, Crossman JE, Gleeson MJ, Cox TCS, Bracey EECML, Strong AJ, Graves P. *Registration of MR and CT images for skull base surgery using point-like anatomical features. Br J Radiology.* 64:1030-1035. 1991

[4] Pelizzari CA, Chen GTY, Spelbring DR, Weichselbaum RR, Chen C-T. *Accurate three dimensional registration of CT, PET and/or MR images of the brain.* J Comput Assist Tomogr 13:20-26. 1989

[5] Jiang H, Robb RA, Holton KS. *New approach to 3-D registration of multimodality medical images by surface matching.* Visualisation in Biomedical Computing, Proc Soc Photo-opt Instrum Eng 1808:196-213. 1992

[6] Hill DLG, Hawkes DJ. *Medical image registration using knowledge of adjacency of anatomical structures.* Image and Vision Computing 12 :173-178 1994

[7] van den Elsen PA. *Multimodality matching of brain images.* J Comp Assis Tomogr 16: 620-633 1992

[8] Woods RP, Cherry SR, Mazziotta JC. *A rapid automated algorithm for accurately aligning and resliceing PET images.* J Comp Assis Tomogr 16: 620-633 1992

[9] Woods RP, Mazziotta JC, Cherry SR. *MRI-PET registration with automated algorithm.* J Comp Assis Tomogr 17: 536-346 1993

[10] Hill DLG, Hawkes DJ, Harrison N, Ruff CF. *A strategy for automated multimodality registration incorporating anatomical knowledge and imager characteristics.* Barrett HH, Gmitro AF, eds. Information Processing in Medical Imaging IPMI '93. Lecture Notes in Computer Science 687 Springer-Verlag, Berlin. pp182-196. 1993

[11] Goldberg DE. *Genetic algorithms in search optimisation and machine learning.* Addison Wesley, Mass. USA. 1989

[12] Lloyd GAS, Barker PG, Phelps PD. *Subtraction gadolinium enhanced magnetic resonance for head and neck imaging.* Br J Radiology 66: 12-16 1993